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Adaptive Non-Linear Bayesian Filter for ECG Denoising

Mitesh Kumar Sao
M.E. Scholar, Electronics & Telecommunication
Shri Shankaracharya Technical Campus
Bhilai, India

Anurag Shrivastava
Assistant Professor, Electronics & Telecommunication
Shri Shankaracharya Technical Campus
Bhilai, India

Abstract—-**The cycles of an electrocardiogram (ECG) signal contain three components P-wave, QRS complex and the T-wave. Noise is present in cardiograph as signals being measured in which biological resources (muscle contraction, base line drift, motion noise) and environmental resources (power line interference, electrode contact noise, instrumentation noise) are normally pollute ECG signal detected at the electrode. Visu-Shrink thresholding and Bayesian thresholding are the two filters based technique on wavelet method which is denoising the PLI noisy ECG signal. So thresholding techniques are applied for the effectiveness of ECG interval and compared the results with the wavelet soft and hard thresholding methods. The outputs are evaluated by calculating the root mean square (RMS), signal to noise ratio (SNR), correlation coefficient (CC) and power spectral density (PSD) using MATLAB software. The clean ECG signal shows Bayesian thresholding technique is more powerful algorithm for denoising.**

Keywords- Discrete Wavelet Transform; ECG signal denoising; Thresholding; Power Line Interference; Signal to Noise Ratio.

I. INTRODUCTION

ECG signals are reflective of electric activities of a heart muscle. They are related to a variety of intertwined and complex chemical, electrical and mechanical processes present in heart. It is one of the best recognized biomedical signals. The ECG signals in their acquisition process are interrupted by various types of noise, such as Power Line Interference, Electrode Contact Noise, Motion Artifacts, Muscle Contraction, Baseline Drift, Instrumentation Noise generated by electronic devices and Electrosurgical Noise. But, the four major types of noises considered are Power Line Interference, Motion artifacts, Muscle contraction and Base Line drift[1] [12].

A. Power Line Interference

From various artifacts contaminate electrocardiogram (ECG) recording, the most common are power line interference and baseline drift. Power line interference is easily recognizable since the interfering voltage in the ECG may have frequency 50 Hz. The interference may be due to stray effect of the alternating current fields due to loops in the patient's cables[2] [9].

B. Motion Artifacts

Movement of the electrode away from the contact area on the skin, leading to variations in the impedance between the electrode and skin causing potential variations in the ECG and usually manifesting themselves as rapid but continuous baseline jumps or complete saturation for up to 0.5 sec. Electrode motion artifact is generally considered the most troublesome, since it can mimic the appearance of ectopic beats and cannot be removed easily by simple filters, as can noise of other types.

C. Muscle contraction

The standard deviation of this kind of noise is 10% of peak to peak ECG amplitude with duration of 50ms and the frequency content being dc to 10kHz. It is induced by the patients movement and is responsible for artifact millivolt level potentials to be generated which is also called EMG (electromyography).

D. Baseline Wander-

The movement of the patient breathing and interaction between the electrodes and skin cause baseline wandering. A cardiologist's eyes become easily fatigued this may inadvertently cause an inaccurate interpretation by observing ECG signal with baseline wandering.

To reduce noise contaminated of the ECG signal, filtering preprocessing is necessary process to preserve useful information. So, the Discrete Wavelet Transform (DWT) is having best suitable choice for ECG signal denoising [15]. Also a literature on comparative study of wavelet denoising algorithm [1]. They use the Discrete Wavelet Transform to decompose signal into coefficients. For these coefficients selection of wavelet thresholding like hard thresholding or soft thresholding is one more task to play a significant role for denoising [8] [11]. There are four different wavelet functions (HAAR, DB2, Sym8, Biorth1.5) are analyzed to eliminate noises from ECG signal [3] [13]. But to improve the efficiency of output result of ECG signal we are applying Adaptive non-linear Bayesian thresholding technique. The Process of denoising of noisy ECG signal [10] is shown in figure [1].

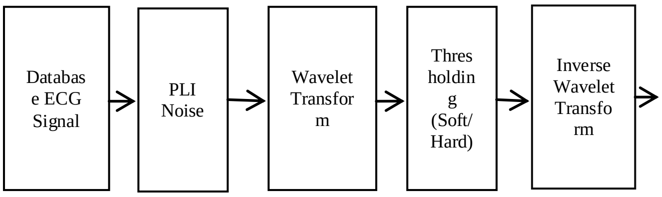

Figure 1. ECG Denoising Process

II. WAVELET TRANSFORM

Wavelets are simply mathematical functions and these functions analyze data according to scale or resolution. They aid in studying a signal at different resolutions or in different windows. The main weakness that was found in Fourier transforms that we could get information about the frequencies present in a signal, but not where and when the frequencies occurred and Wavelet Transform give all the information about it. Wavelet Transform do a better job in approximating signals with sharp spikes or signals having discontinuities whereas Fourier transform does not give efficient results.

A. Continuous Wavelet Transform

Here, $f(t)$ is a one dimensional function taking positive or zero values.

$$C(a,b) = \int_{-\infty}^{+\infty} f(t)\,\varphi_{a,b}(t)dt \qquad (1)$$

Wavelet (frame tight frame, biorthogonal, orthogonal basis) *a*- scale, *b*-translation

$$\varphi_{a,b}(t) = a^{-\frac{1}{2}}\varphi\left(\frac{t-b}{a}\right) \qquad (2)$$

B. Discrete Wavelet Transform

The finite scale multi resolution representation of a discrete function can be known as a discrete wavelet transform (DWT). Discrete wavelet transform is invertible and orthogonal, where the inverse transform expressed as a matrix is the transpose of the transform matrix. In terms of the wavelet coefficients, the wavelet equation is

$$\psi(x) = \sum_{k}^{N-1} h_k\sqrt{2\phi(2x-k)} \qquad (3)$$

Here, $h_k = h_0, h_1, h_2, \ldots.$ are high pass wavelet coefficients.

where ψ is wavelet function and k is integer that scale and dilate the wavelet basis or function. The factor 'k' provides the position. The wavelet function is dilated by powers of two and it is translated by the integer *k*.

Scaling equation in terms of the scaling coefficients is given as shown below,

$$\phi(x) = \Sigma_k^{N-1}\, g_k\sqrt{2\phi(2x-k)} \qquad (4)$$

Where the function $\phi(x)$ is scaling function and the coefficients $g_k = g_0, g_1, g_2, \ldots..$ are low pass coefficients.

DWT decomposes the signal into an approximation coefficients (CA) and detail coefficients (CD). Approximation coefficients are corresponding the LPF coefficients and detail coefficients are corresponding the HPF coefficients shown in Figure[2]. Furthermore, the CA is consequently divided into new approximation and detailed coefficients.

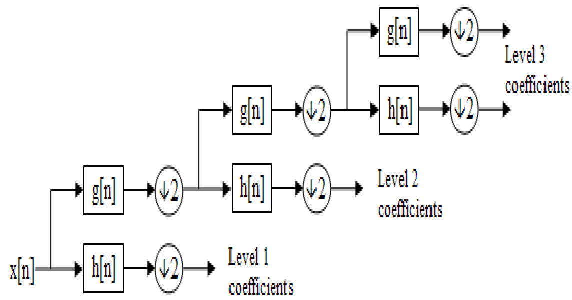

Figure 2. Filter bank structure of DWT

The signal is reconstructed from the modified coefficients. This process is also known as the inverse discrete wavelet transform (IDWT) [5] [7].

III. WAVELET THRESHOLDING

Selection of thr\eshold is an important point of interest. It should be taken so as to preserve the edges of the denoised signal. Some typically used methods for denoising signal are Visu Shrink, Sure Shrink, Bayes Shrink [6]. It is important to know about the two general categories of thresholding. They are hard- thresholding and soft-thresholding types [1] .

A. Hard Thresholding

The hard-thresholding T_H can be defined as

$$T_H = \begin{cases} x & for\ |x| > t \\ 0 & in\ all\ the\ regions \end{cases} \qquad (5)$$

Here t is threshold value. Plot for this is as shown below

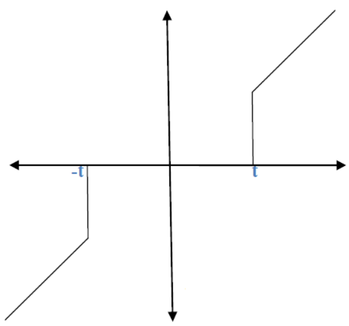

Figure 3. Hard Thresholding

In this, all coefficients whose magnitude is greater than the selected threshold value *t* remain same and the others whose magnitude is smaller than *t* are set to zero. It creates a region around zero where the coefficients are considered negligible [4].

B. Soft Thresholding

In Soft thresholding the coefficients whose magnitude is greater than the selected threshold value are become shrinks towards zero and others set to zero.

The Soft-thresholding T_s can be defined as

$$T_s = \begin{cases} sgn(x)(|x|-t) & for\ |x|>t \\ 0 & in\ all\ other\ region \end{cases} \quad (6)$$

It can be seen that the soft method is much better and yields more visually pleasant signal. This is because the hard method is discontinuous and yields abrupt artifacts in the recovered signals. Also, the soft method yields a smaller minimum mean squared error compared to hard form of thresholding [4].

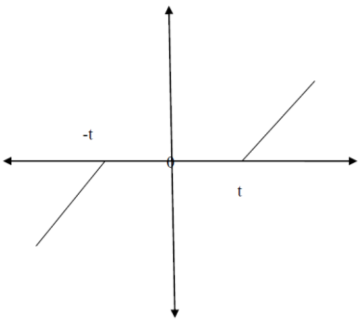

Figure 4. Soft Thresholding

IV. ALGORITHM

The proposed threshold $T_B(\sigma_X)$ in general case, but the optimal threshold $T^*(\sigma_X, \beta)$ for given fixed β. The threshold T_B depends only on the standard deviation and not on the shape parameter β. The wavelet coefficients typical values of β falls in range [0.5, 1] this simple form of the threshold T_B is appropriate for purpose.

The estimation of Noise Variance σ^2 is necessary.

$$\hat{\sigma} = \frac{Median(|Y_{ij}|)}{0.6745}, \quad Y_{ij} \in subband\ HH_1 \quad (7)$$

The parameter β does not explicitly enter into the expression of $T_B(\sigma_X)$, only the signal standard deviation σ_X does.

$$\sigma_Y^2 = \sigma_X^2 + \sigma^2 \quad (8)$$

σ_Y^2 can be found empirically by:

$$\hat{\sigma}_Y^2 = \frac{1}{n^2}\sum_{i,j=1}^{n} Y_{ij}^2 \quad (9)$$

$$\hat{T}_B(\hat{\sigma}_X) = \frac{\hat{\sigma}^2}{\hat{\sigma}_X} \quad (10)$$

here, $\hat{\sigma}_X = \sqrt{\max}\ (\hat{\sigma}_Y^2 - \hat{\sigma}^2, 0)$

In the case that $\hat{\sigma}^2 \geq \hat{\sigma}_Y^2$, $\hat{\sigma}_X$ is taken to be 0, that is $\hat{T}_B(\hat{\sigma}_X)$ is ∞ , or, in practice, $\hat{T}_B(\hat{\sigma}_X) = \max(|Y_{ij}|)$, all coefficients are set to 0.

$$\hat{T}_B(\hat{\sigma}_X) = \frac{\hat{\sigma}^2}{\hat{\sigma}_X} \quad (11)$$

To summarize our method as *BayesShrink* this performs soft thresholding, with the data-driven subband-dependent threshold.

V. RESULTS

To measure denoising performance some parameters are calculated from each thresholding algorithm with wavelet families and results shown in the form of comparative tables. Also the output result of matlab programming is shown in different figures. Finally, figure [10] shows the denoised signal with overlap of original ECG signal.

TABLE I. DENOISING RESULT FOR PLI NOISE WITH HAAR WAVELET FAMILY

Database	Visu-Shrink Thresholding Filter					Bayesian Thresholding Filter				
	RMSE		SNR (dB)		CC	RMSE		SNR (dB)		CC
	Hard	Soft	Hard	Soft		Hard	Soft	Hard	Soft	
Sample 1	8.6600	8.5751	15.4056	15.4912	0.9862	8.2928	6.0650	15.7819	18.4994	0.9929
Sample 2	8.6603	8.6751	10.0081	9.9932	0.9537	6.1215	6.4230	13.0216	12.6039	0.9722
Sample 3	8.6603	8.6325	18.1694	18.1973	0.9925	8.5396	6.4523	18.2913	20.7258	0.9958
Sample 4	8.6604	8.5737	20.0500	20.1374	0.9952	8.6055	6.8041	20.1052	22.1453	0.9969
Sample 5	8.6603	8.7187	9.2616	9.2032	0.9442	7.8489	7.6302	10.1160	10.3615	0.9529

TABLE II. DENOISING RESULT FOR PLI NOISE WITH DB2 WAVELET FAMILY

Database	Visu-Shrink Thresholding Filter					Bayesian Thresholding Filter				
	RMSE		SNR (dB)		CC	RMSE		SNR (dB)		CC
	Hard	Soft	Hard	Soft		Hard	Soft	Hard	Soft	
Sample 1	8.6601	8.5405	15.4055	15.5263	0.9863	7.2404	5.8448	16.9607	18.8205	0.9934
Sample 2	8.6603	8.6225	10.0080	10.0460	0.9542	6.1837	5.4493	12.9338	14.0318	0.9800
Sample 3	8.6603	8.7438	18.1694	18.0860	0.9924	8.4691	6.0360	18.3633	21.3051	0.9963
Sample 4	8.6599	8.4080	20.0505	20.3069	0.9953	8.4623	6.0652	20.2510	23.1438	0.9976
Sample 5	8.6603	8.6236	9.2616	9.2984	0.9453	7.5599	7.4217	10.4419	10.6022	0.9555

TABLE III. DENOISING RESULT FOR PLI NOISE WITH SYM8 WAVELET FAMILY

Database	Visu-Shrink Thresholding Filter					Bayesian Thresholding Filter				
	RMSE		SNR (dB)		CC	RMSE		SNR (dB)		CC
	Hard	Soft	Hard	Soft		Hard	Soft	Hard	Soft	
Sample 1	8.6602	8.5857	15.4054	15.4804	0.9862	7.7227	5.7368	16.4006	18.9826	0.9937
Sample 2	8.6603	8.6451	10.0080	10.0232	0.9539	5.0308	5.3774	14.7259	14.1473	0.9806
Sample 3	8.6603	8.6588	18.1694	18.1709	0.9925	8.3988	5.7467	18.4357	21.7317	0.9966
Sample 4	8.6606	8.5162	20.0498	20.1959	0.9952	7.9292	5.4901	20.8162	24.0092	0.9980
Sample 5	8.6603	8.8036	9.2616	9.1190	0.9433	7.0770	7.3034	11.0153	10.7418	0.9569

TABLE IV. DENOISING RESULT FOR PLI NOISE WITH BIORTH1.5 WAVELET FAMILY

Database	Visu-Shrink Thresholding Filter					Bayesian Thresholding Filter				
	RMSE		SNR (dB)		CC	RMSE		SNR (dB)		CC
	Hard	Soft	Hard	Soft		Hard	Soft	Hard	Soft	
Sample 1	8.6600	8.5635	15.4056	15.5029	0.9862	8.2763	5.8567	15.7992	18.8029	0.9934
Sample 2	8.6603	8.6660	10.0081	10.0023	0.9537	5.8878	6.2478	13.3597	12.8441	0.9738
Sample 3	8.6603	8.6310	18.1694	18.1988	0.9925	8.5589	6.3806	18.2717	20.8228	0.9959
Sample 4	8.6605	8.5690	20.0498	20.1422	0.9952	8.6091	6.6922	20.1016	22.2893	0.9970
Sample 5	8.6603	8.7198	9.2616	9.2022	0.9442	7.7743	7.5687	10.1990	10.4318	0.9538

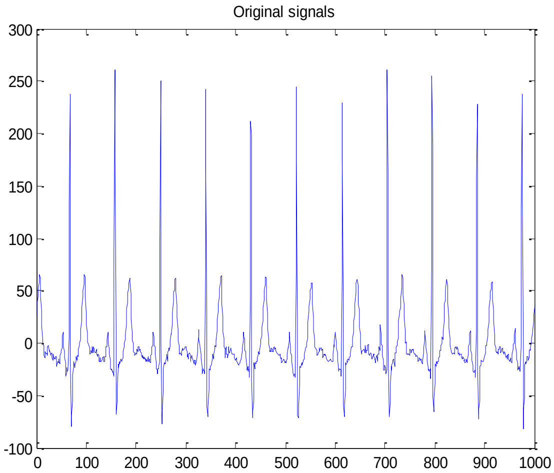

Figure 5. Original ECG Signal

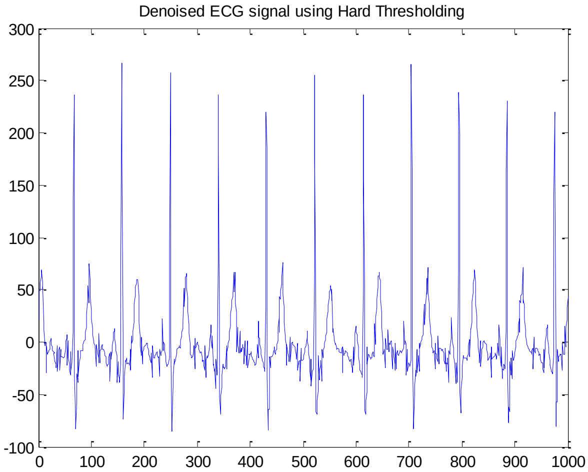

Figure 7. Denoised ECG signal using Hard Thresholding

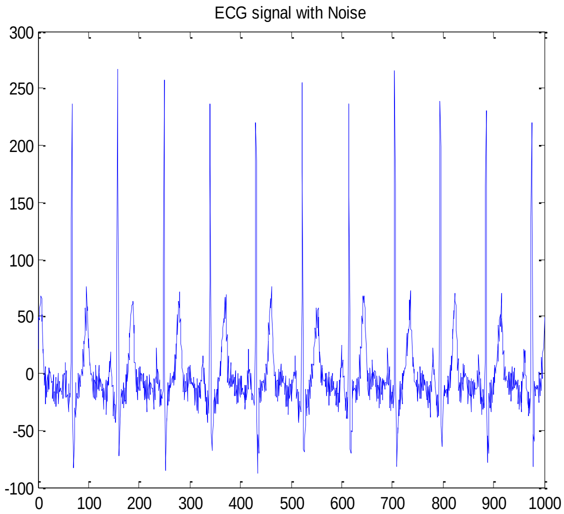

Figure 6. Noisy ECG Signal

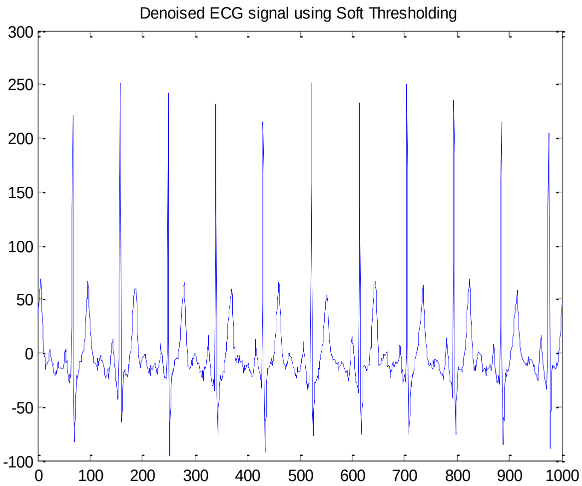

Figure 8. Figure 8: Denoised ECG signal using Soft Thresholding

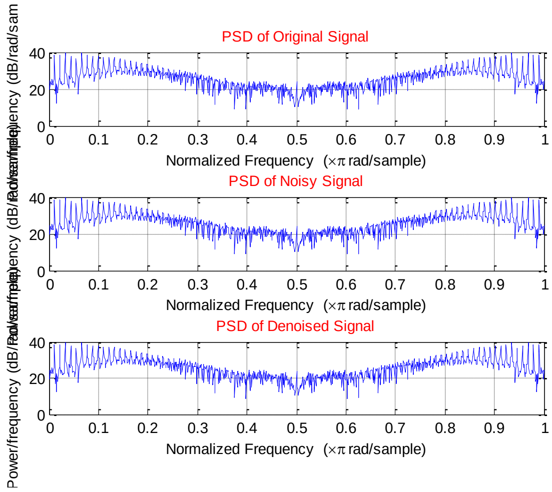

Figure 9. PSD signal

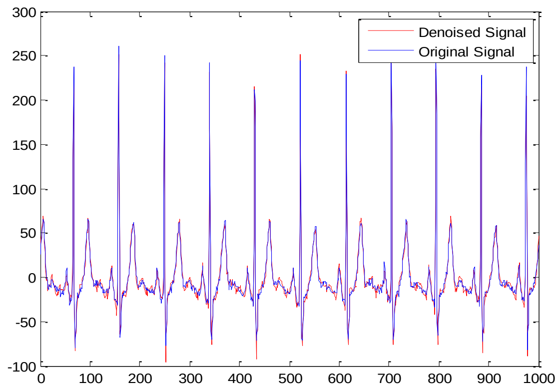

Figure 10. Denoised ECG Signal

VI. CONCLUSION

The discrete wavelet transform allows processing of non-stationary signals such as ECG signal. One dimensional wavelet analysis with different four wavelet families (HAAR, Db2, Sym8, Biorth1.5) based are used to extract the original ECG signal from power line interference noisy signal. The comparative analysis was carried out on the ECG data record and summarizes the obtained output RMSE, SNR and CC values for hard, soft and improved thresholding denoising methods respectively. We concluded that proposed Adaptive non-linear Bayesian thresholding technique is superior to other thresholding technique in many aspects such as smoothness geometrical characteristics of original ECG signal and also better SNR value.

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